https://doi.org/10.17221/296/2024-AGRICECON

How does climate shock affect technology adoption in rice production?

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Citation: Nguyen T.P., Nguyen D.K., Truong Q.D. (2025): How does climate shock affect technology adoption in rice production? Agric. Econ. – Czech, 71: 14–26.

Abstract: The objective of the study is to determine the impact of shock from climate change, such as drought and flood, on various technology adoptions in rice production in Vietnam. This study utilised VARHS (The Vietnam Access to Resources Household Survey) panel data from 2012 to 2018 and employed regression analysis following the application of propensity score matching (PSM) to address potential selection bias caused by drought and flood shocks. The findings indicated that households tend to adopt the improved variety of rice and organic fertilisers since households suffer the shock from the drought. Another finding showed that households used more chemical fertiliser and reduced the probability of using improved seeds in rice production since the household was affected by floods. Based on the findings, policies should prioritise promoting and implementing environmentally friendly farming methods that are customised to address specific climate-related difficulties.

Keywords: drought; flood; innovation; propensity score matching; risk uncertainty

The farmers can increase the adoption of better agricultural innovation to enhance productivity and make their and the nation's food basket bulkier, thus ensuring food security and encouraging inclusive growth and poverty reduction (Ambong 2022; Phan et al. 2022a). Modern services and climatically appropriate technologies in agriculture can enable agricultural production systems to adjust to the variations in weather and climate change (Asfaw et al. 2012). Precision agriculture technology compatibility and farmer skills help facilitate adoption (Shi et al. 2022). Although the advantages of agricultural technologies are frequently mentioned and significant attempts are made to persuade farmers to invest in them, the adoption rates remain low in rural regions of developing countries. The adoption of agricultural technology is complicated and influenced by several factors (Farooq et al. 2019). Credit, risk, organisational belonging, access to development projects, and uncertainty influence agricultural innovation adoption (Usman et al. 2021; Wang et al. 2021; Li et al. 2023). Labour-saving technologies in agriculture also emphasise non-pecuniary benefits, including reduced management effort, increased safety, and environmental considerations (Zhang et al. 2023). Cli-

This research is partly funded by the University of Economics, Hue University under grant No. NNC.DHKT.2024.08

https://doi.org/10.17221/296/2024-AGRICECON

mate shocks, including extreme weather occurrences, can significantly diminish agricultural productivity, compelling farmers to implement agricultural technologies to alleviate these effects (Mehar et al. 2016; Holden and Quiggin 2017; Tambo and Wünscher 2017; Michler et al. 2019). In Vietnam, where the adoption of numerous agricultural advancements remains limited, and the issues of food insecurity and poverty persist as significant obstacles to the increase of productivity and sustainable human development. The low adoption rate can be linked to several variables, such as the specific features of individual farmers, inadequate infrastructure, market imperfections, insufficient institutional support, climate shocks, and pricing hazards (Asfaw and Admassie 2004; Hossain et al. 2006; Mehar et al. 2016; Holden and Quiggin 2017; Kumar et al. 2020; Tesfay 2021; Belayneh 2023).

Insufficient financial resources can hinder technology use, including acquiring genetically modified seeds, fertiliser (chemical fertiliser and organic fertilisers), and irrigation (Branco and Féres 2021). Rural households encounter several risks related to markets, production, and health, primarily resulting from common occurrences such as a rise in the cost of agricultural inputs, crop failure caused by drought, crop diseases and pest infestations, and illness among family members (Komarek et al. 2020). These shocks might adversely impact food production, household income, and household assets (Arslan et al. 2017; Asfaw et al. 2019; Grabrucker and Grimm 2021). In addition, they can modify the time frame within which households plan for the future, as well as the individual rates at which they discount future benefits (Emmanuel et al. 2016). This case can lead to a decrease in the rate of technology adoption. Moreover, embracing agricultural advances can serve as both a proactive approach to managing unexpected events and a reactive response to such events (Bukchin and Kerret 2018). While it may be challenging to identify these techniques during rehearsal specifically, the goal of the study is to determine if the adoption of agricultural innovations is influenced by the climate shocks experienced by the households in Vietnam since the country is particularly vulnerable to climate change due to its geographical features, including a long coastline and wide river basins, which expose it to increasing sea levels, extreme weather events, and other environmental stresses (Ha et al. 2022; Kien et al. 2023). The importance of implementing agricultural innovations in reaction to climatic shocks is a worldwide issue that surpasses geographical limits. Other nations can adopt successful methods to bolster agricultural resilience, guarantee food security, and foster sustainable development in response to climate change by drawing lessons from the experiences of countries such as Vietnam.

The impact of climate shocks on household wellbeing is pivotal for agricultural and economic growth in developing countries. When households face unexpected disruptions like agricultural or climatic disturbances, they often encounter barriers to adopting innovative and potentially more profitable farming practices. This tendency arises because households typically opt for low-risk, low-return activities to navigate shocks and avoid falling into poverty traps. Households employ various coping mechanisms to recover from such events. These include utilising savings in the form of money, crops, or animals, borrowing from informal credit sources, reallocating household members to wage labour, and leveraging social networks like 'equb' and 'idir' for financial aid during crises (Gebremariam and Tesfaye 2018). Developing these coping strategies is crucial for stabilising household income fluctuations and building resilience, which can eventually facilitate the adoption of advanced agricultural technologies and methods. Previous research indicates that while farming risks from climate change can reduce earnings, funds from alternative sources provide the necessary liquidity to offset losses, thereby linking shocks, income diversification, and the adoption of improved farming technologies (Gebremariam and Tesfaye 2018; Tan et al. 2021). The unpredictable nature of shocks can both hinder and spur the adoption of new agricultural advancements that require capital, such as high-quality seeds or fertilisers. Moreover, research yields mixed results regarding the effect of shocks on technology adoption. Gebremariam and Tesfaye (2018) and Diagne et al. (2022) suggest that while shocks may prompt farmers to adopt technology in response to the shocks from climate change, such as drought and flood, they can also reduce household income and dampen the likelihood of technology adoption.

Understanding the nuances of coping strategies and their impact on household resilience is vital for policymakers and development practitioners. Previous studies emphasise the variability in coping styles and their outcomes in subsequent shocks, underscoring the need for diverse coping strategies and adaptable agricultural technology frameworks. Importantly, comprehending how households cope with shocks and the implications for technology adoption is crucial for designing effective agricultural policies and interventions

https://doi.org/10.17221/296/2024-AGRICECON

in developing countries. This paper aims to find the effect of shocks from climate change, such as drought and flood, on technology adoption, including chemical fertiliser, improved seeds, organic fertiliser prepared by households, and organic fertiliser bought from others in rice production in Vietnam. In addition, the study aims to answer the question: 'What is the difference in farmer behaviour in response to drought and floods?'. Understanding the differences in farmer behaviour in response to drought and floods is essential for developing effective agricultural policies and support systems. The finding is not only significant for Vietnam but also for developing countries. Using a mix of propensity score matching (PSM) and fixed effect estimation to alleviate the endogenous problem of suffering climate shock, the results demonstrate that households choose to adopt improved varieties and organic fertilisers as a response to the drought. Another research indicates that households use more chemical fertiliser, and reduce the likelihood of utilising improved seeds in rice cultivation since the household is harmed by floods. The findings contribute uniqueness and depth to the link between climate shock and technology adoption in rice production.

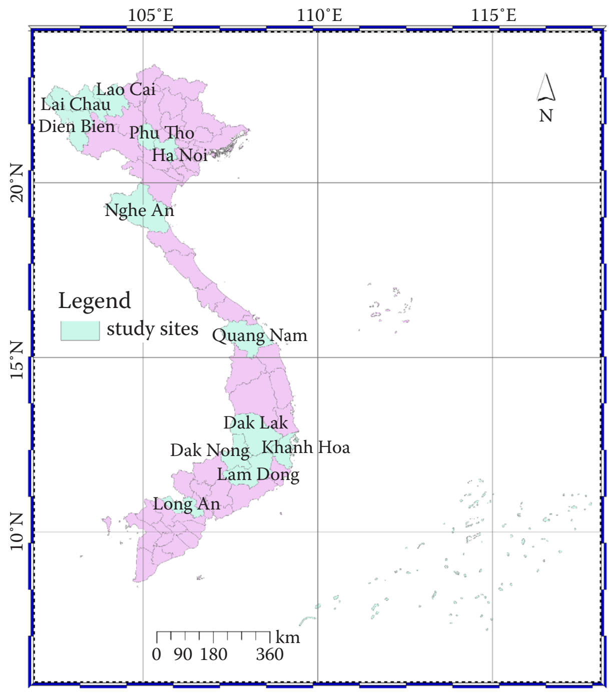

Figure 1. Study sites from VARHS in rural Vietnam

VARHS – The Vietnam Access to Resources Household Survey
Source: Phan et al. (2022a)

MATERIAL AND METHODS

Data source. The Vietnam Access to Resources Household Survey (VARHS) is a comprehensive dataset compiled between 2008 and 2018 (UNU Wider 2024). It provides detailed information on the socioeconomic status and availability of household resources in Vietnam. Data collection involves gathering information on households affected by climate change shocks, starting from 2012. Hence, this analysis utilised panel data from the VARHS covering the period from 2012 to 2018, with two years of data for each year. To obtain a precise understanding of the conditions of households in all regions of Vietnam, it was imperative to gather responses to many questions posed in the VARHS survey from the 12 provinces comprising the country. Figure 1 displays the precise locations of the research sites. The sites encompassed the northern region, consisting of Ha Tay, Lao Cai, Phu Tho, Lai Chau, and Dien Bien. Additionally, there were Middle regions sites, which include Nghe An, Quang Nam, Khanh Hoa, Dak Lak, Dak Nong, and Lam Dong. Lastly, there was the Mekong River region, namely Long An.

Table 1 indicates the dependent and independent variables that were used in the estimation process of the relationship between shocks from climate change (drought and flood) and technology adoption (chemical fertiliser, improved seed, organic fertiliser prepared by household, and organic fertiliser bought from others) in rice production in Vietnam. The independent variables include the shocks from climate change (drought and flood), technology adoption (chemical fertiliser, improved seed, organic fertiliser prepared by household, and organic fertiliser bought from others), household characteristics (gender of household head, age of household head, educational level of household head, health risks, number of family members, access to credit, access to the Internet, access to agricultural extension service, access to irrigation, number of assets), land fragmentation index (Simpson index and number of plots), farm characteristics (changing land quality, soil and water conservation, and rice production area).

Table 1 provides the changes in the number of experienced shocks, several technology adoptions, household characteristics, and farm characteristics. Chemical fertiliser adoption was high across all years, rising from 0.96 in prior years to 0.99 in 2018, with little decrease in variability (standard deviation falls from 0.20 to 0.10). In 2018, improved seed adoption reached 0.90, up marginally. Organic fertiliser adoption pre-

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Table 1. Descriptive statistics of samples

Variable	2012		2014		2016		2018		All	
	mean	SD	mean	SD	mean	SD	mean	SD	mean	SD
Adoption of chemical fertiliser (1 = yes; 0 = no)	0.96	0.20	0.96	0.19	0.96	0.20	0.99	0.10	0.97	0.18
Adoption of improved seeds (1 = yes; 0 = no)	0.84	0.37	0.87	0.34	0.82	0.39	0.90	0.30	0.86	0.35
Adoption of organic fertiliser prepared by household (1 = yes; 0 = no)	0.51	0.50	0.46	0.50	0.43	0.50	0.29	0.45	0.42	0.49
Adoption of organic fertiliser bought from others (1 = yes; 0 = no)	0.21	0.41	0.16	0.36	0.21	0.41	0.15	0.35	0.18	0.38
Shock from drought (1 = yes; 0 = no)	0.15	0.35	0.11	0.32	0.04	0.20	0.07	0.25	0.10	0.30
Shock from flood (1 = yes; 0 = no)	0.18	0.39	0.20	0.40	0.23	0.42	0.12	0.32	0.18	0.39
Gender of household head (1 = male; 0 = female)	0.84	0.37	0.82	0.38	0.81	0.39	0.78	0.41	0.81	0.39
Age of household head (years)	51.84	11.49	53.45	11.50	55.06	11.52	56.56	11.20	54.23	11.56
Educational level of the household head (years)	7.83	3.16	8.51	3.02	8.80	2.86	7.89	3.25	8.26	3.10
Health risks (1 = yes; 0 = no)	0.04	0.20	0.05	0.23	0.03	0.18	0.04	0.20	0.04	0.20
Number of family members	4.68	1.65	4.61	1.64	4.48	1.67	4.35	1.81	4.53	1.70
Access to credit (1 = yes; 0 = no)	0.46	0.50	0.40	0.49	0.31	0.46	0.28	0.45	0.36	0.48
Access to the Internet (1 = yes; 0 = no)	0.40	0.49	0.44	0.50	0.44	0.50	0.57	0.50	0.46	0.50
Access to the agricultural extension service (1 = yes; 0 = no)	0.58	0.49	0.59	0.49	0.44	0.50	0.42	0.49	0.51	0.50
Access to irrigation (1 = yes; 0 = no)	0.96	0.19	0.98	0.15	0.96	0.20	0.99	0.08	0.97	0.16
Number of assets	6.84	3.22	7.80	3.35	7.62	3.52	8.06	3.47	7.58	3.42
Rice production area[1]	7.79	0.91	7.75	0.93	7.72	0.95	7.66	0.99	7.73	0.95
Fragmentation index (Simpson index)	0.55	0.27	0.51	0.28	0.49	0.28	0.44	0.29	0.50	0.28
Number of plots	5.85	2.76	5.31	2.77	4.88	2.66	4.52	2.44	5.14	2.71
Changing land quality (1 = yes; 0 = no)	0.03	0.18	0.05	0.21	0.04	0.20	0.03	0.17	0.04	0.19
Soil and water conservation (1 = yes; 0 = no)	0.31	0.46	0.15	0.36	0.19	0.39	0.27	0.44	0.23	0.42

[1]in log form
Source: Author's elaboration

pared by households dropped from 0.51 in 2012 to 0.29 in 2018, showing a shift away from organic fertilisers. Organic fertiliser purchased from others was rarely used, declining from 0.21 in 2012 to 0.15 in 2018. The mean drought shock frequency decreased from 0.15 in 2012 to 0.07 in 2018. Flood shocks peaked at 0.23 in 2016 and dropped to 0.12 in 2018. The household head's gender, age, and education also changed significantly over time. Credit, Internet, agricultural extension services, and irrigation access were also altered. Access to credit decreased from 0.46 in 2012 to 0.28 in 2018, and Internet access increased to 0.57 in 2018, indicating digital connectivity. The figure for access to agricultural extension service dropped from 0.58 in 2012 to 0.42 in 2018, showing less outreach and utilisation. After peaking at 0.99 in 2018, irrigation adoption remained high, indicating effective water use. Regarding land and agriculture rice production dropped from 7.79 in 2012 to 7.66 in 2018. The Simpson index dropped from 0.55 in 2012 to 0.44 in 2018, showing agricultural plot consolidation. Less fragmentation was seen in 2018, with 4.52 plots per residence compared to 5.85 in 2012. Adoption of soil and water conservation peaked at 0.31 in 2012 and fell to 0.27 in 2018. The

https://doi.org/10.17221/296/2024-AGRICECON

mean household asset ownership has increased from 6.84 in 2012 to 8.06 in 2018. The number of family members showed a decrease in household size from 4.68 in 2012 to 4.35 in 2018.

Methodology. The use of ordinary least squares (OLS) regression in the presence of endogeneity in shock from climate change, such as drought or flood, provides biased results and an underestimation of the impact of shocks on technology adoption (Tran and Van Vu 2019). In the absence of empirical evidence, non-experimental techniques such as instrumental variable (IV), propensity score matching (PSM), difference-in-differences (DID), or a combination of PSM and DID were crucial for assessing the average treatment effect on the treated (ATT) (Nguyen et al. 2024).

Instrumental variables (IVs) are frequently employed to address selection bias resulting from unobservable factors. For IVs to have a significant impact, it should be associated with climate shocks, but it should not directly determine the technology adoption. Nevertheless, the task of locating dependable IVs is arduous and might lead to biased results if executed improperly. Based on previous research (Duong and Thanh 2019; Nguyen Chau and Scrimgeour 2022), the study selected a combination of PSM and fixed effect estimation as a more appropriate approach to address selection bias.

This study employed propensity score matching, a statistical technique that mitigates selection bias and enabled the construction of a plausible counterfactual scenario by utilising observed characteristics of households that did not suffer shock from climate change. In the realm of PSM methodology, a vital component entails the delineation of the common support region. The term 'common support' pertains to the extent of values in the propensity scores when both the treated group (households suffering shock from drought or flood) and the control group (households not suffering shock) are present (Abate et al. 2014). Estimating the treatment impact becomes challenging for households that suffer shock and have propensity scores that fall outside the common support zone. It is important to limit the matching process to homes that are located in the same common support region. Deviating from this constraint introduces a significant bias because it involves comparing households that cannot be reliably compared (Heckman et al. 1997). In addition, the implementation of common support limitations often improves the reliability of estimates, decreases the chances of inadequate matches, and boosts the quality of matches (Abate et al. 2014; Duong and Thanh 2019).

It is crucial to recognise that standard propensity score matching, when used with cross-sectional data, has limits in its capacity to mitigate selection biases solely based on observable covariates. This implies that unobserved variations across people can still influence both the implementation of the intervention and the subsequent consequences. Therefore, it is essential to employ panel data, where the integration of fixed effect regression and matching is seen as a more favourable methodological approach (Becker and Ichino 2002; Khandker et al. 2009). Unlike normal propensity score matching, this technique not only accounts for reported covariates but also includes time-invariant unobserved components, resulting in a more dependable analytical framework.

The following logit model with a set of matched covariates that assist in predicting households suffering shock from climate change was used to estimate the propensity score.

$$Shock_{it} = \lambda X_{it} + \chi HID_{it} + S_t + \varepsilon_{ist} \quad (1)$$

where: $Shock_{it}$ – binary variable that takes the value of 1 if a household experiences a shock from climate change (drought or flood) and 0 otherwise; X_{it} – set of explanatory factors mentioned in Table 1; HID_{it} – household fixed effect; S_t – year fixed effect; ε_{ist} – error term.

Equation (1) was utilised to estimate two separate estimations: *i*) variables associated with the impact of drought, and *ii*) variables associated with the impact of flood.

A household affected by climate change was subsequently paired with a non-affected household. The study examines the nearest neighbour matching method, as it was anticipated to yield the least bias (Nguyen Chau and Scrimgeour 2022). This study used the following model to assess the impact of shock from climate change on technology adoption in rice production:

$$Y_{it} = Shock_{it} + \lambda X_{it} + \chi HID_{it} + S_t + \varepsilon_{it} \quad (2)$$

where: Y_{it} – technology adoption such as chemical fertiliser, improved seeds, organic fertiliser prepared by households, and organic fertilizer bought from others; $Shock_{it}$ – binary variable that equals 1 if a household suffers sock from climate change (drought or flood) and 0 otherwise; X_{it} – vector of control variables that includes individual characteristics and household characteristics mentioned earlier; HID_{it} – household fixed effect; S_t – year fixed effect; ε_{it} – error term.

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RESULTS AND DISCUSSION

Results. The study begins by describing the systematic differences between the treatment group and the control group. Tables 2 and 3 provide a succinct summary of the specific agricultural characteristics utilised in the model. Additionally, the analysis involved conducting balance tests on each covariate before and after matching, for both the unpaired and matched groups. After the matching procedure, most of the covariate means in the treatment and control groups do not show significant differences (Tables 2 and 3). These data show that, after the matching process, the factors influencing the shock from drought or flood were distributed more evenly, reducing the endogeneity problem.

Propensity score matching (PSM) utilises the propensity score to balance the pre-treatment characteristics of the treatment (suffering shocks) and control (not suffering shocks) groups. The initial step involves assessing the convergence of the propensity score distributions for both groups. After doing the matching technique, the distributions of the propensity scores are illustrated in Figure 2 for shock from drought and Figure 3 for shock from flood. Neither of the two graphs exhibits a notable accumulation in probability at 0 or 1. Furthermore, the calculated densities exhibit significant similarity, and their primary masses coincide. Therefore, there is no proof of a breach of the overlap assumption. The study presents the distribution of the propensity score both before and following the matching process, as illustrated in Figure 2. Before matching, the distributions of the propensity scores for experienced shock (represented by the blue line) and non-experienced shock (represented by the black line) due to drought exhibit differences. Following the application of PSM, the propensity score distributions of both groups exhibited similarity. Likewise, Figure 3 presents comparable propensity scores for the two groups (those who experienced shocks and those who did not) following the application of propensity score matching (PSM). Table 4 presents the findings about the influence of shock from drought on the technology adoption in rice production, employing both ordinary least squares with and without PSM estimation.

OLS estimations without matching reveal that households suffering shock from drought increase the probability of technology adoption, such as improved seeds, and organic fertilisers bought from others. The coefficient of influence of shock from drought on technology adoption, such as improved seeds of rice variety and organic fertiliser bought from others, from OLS

Table 2. Balance tests comparing unmatched and matched samples for shocks from drought

Variables	Unmatched			Matched		
	treatment	control	*P*-value	treatment	control	*P*-value
Access to credit	0.368	0.437	0.047	0.368	0.424	0.201
Access to Internet	0.444	0.436	0.814	0.444	0.460	0.720
Gender of household head	0.844	0.824	0.443	0.844	0.844	1.000
Age of household head	52.824	53.239	0.598	52.824	52.944	0.906
Educational level of the household head	8.288	8.329	0.851	8.288	8.204	0.766
Number of assets	6.740	7.395	0.005	6.740	7.864	0.000
Rice production area[1]	7.740	7.781	0.518	7.740	7.802	0.444
Fragmentation index	0.478	0.505	0.175	0.478	0.519	0.117
Changing land quality	0.080	0.043	0.013	0.080	0.056	0.287
Number of plots	5.552	5.356	0.300	5.552	5.724	0.480
Access to the agricultural extension service	0.540	0.556	0.645	0.540	0.556	0.720
Soil and water conservation	0.364	0.226	0.000	0.364	0.332	0.454
Access to irrigation	0.960	0.969	0.456	0.960	0.948	0.523
Health risks	0.036	0.093	0.003	0.036	0.060	0.210
Number of family members	4.540	4.600	0.619	4.540	4.776	0.113
Observation	250	1 107	–	187	216	–

[1]in log form

Source: Author's elaboration

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Table 3. Balance tests comparing unmatched and matched samples for shocked from flood

Variables	Unmatched			Matched		
	treatment	control	*P*-value	treatment	control	*P*-value
Access to credit	0.459	0.420	0.383	0.459	0.348	0.063
Access to Internet	0.422	0.439	0.710	0.422	0.430	0.902
Gender of household head	0.911	0.818	0.007	0.911	0.837	0.067
Age of household head	52.274	53.260	0.333	52.274	52.659	0.777
Educational level of the household head	7.615	8.400	0.006	7.615	7.941	0.390
Number of assets	7.837	7.212	0.039	7.837	7.052	0.049
Rice production area[1]	7.817	7.768	0.556	7.817	7.815	0.985
Fragmentation index	0.524	0.497	0.296	0.524	0.565	0.206
Changing land quality	0.059	0.048	0.578	0.059	0.059	1.000
Number of plots	5.193	5.414	0.365	5.193	5.963	0.022
Access to the agricultural extension service	0.770	0.529	0.000	0.770	0.637	0.016
Soil and water conservation	0.274	0.249	0.524	0.274	0.267	0.892
Access to irrigation	0.978	0.966	0.480	0.978	0.919	0.028
Health risks	0.030	0.088	0.018	0.030	0.030	1.000
Number of family members	4.452	4.604	0.327	4.452	4.511	0.756
Observation	135	1 222	–	99	143	–

[1]in log form
Source: Author's elaboration

with matching is higher compared to the estimates obtained through OLS without matching. The result implies that households tended to increase their adoption of improved seeds and organic fertiliser since the households facing the shocks from climate change, such as drought, with the effect of the coefficient are 0.078 and 0.061, respectively. In addition, the results show that the correlation between shock from drought and technology, such as chemical fertiliser and organic fertiliser prepared by households in rice production, was not significant.

Furthermore, Table 4 presents some factors that affect technology adoption. Regarding the adoption of chemical fertilisers, the result indicates that a household with male head uses more chemical fertilisers than others, with a coefficient of 0.133 and a significance level of 5%. Similarly, rice production areas have a positive correlation with the adoption of chemical fertilisers at a significant level of 5%. This means that households with a large scare of rice production tend to use chemical fertiliser. Additionally, households with access to irrigation tend to adopt more chemical fertilisers than others. Access to credit was one of the factors that affected the adoption of improved seeds. An increase in accessing credit improves the probability of improved variety adoption with a coefficient of 0.064 at a significant level of 10%. However, farms with access to credit reduced the probability of technology adoption such as organic fertiliser. In addition, a young farmer tended to adopt more organic fertiliser than the older. Besides, practices of soil and water conservation did not encourage rice farms to apply more improved seeds. Table 5 presents the effect of shock from the flood on several technology adoptions, such as fertiliser chemicals, improved seeds, organic fertilisers prepared by households, and organic fertilisers bought from others, employing both ordinary least squares with and without PSM estimation. The result shows that shock of flood had significant impact on the technology adoption of farm rice, such as chemical fertilisers and improved seeds. However, the study does not provide a significant relationship between shock from flood and technology adoption, such as organic fertiliser. In particular, OLS estimations without matching revealed that households suffering shock from flood had an increased probability of technology adoption, such as chemical fertilisers. The coefficient of influence of shock from flood on technology adoption, such as chemical fertilisers, by OLS with matching was higher compared to the estimates obtained through OLS without matching. The result implied that households tended to increase their adop-

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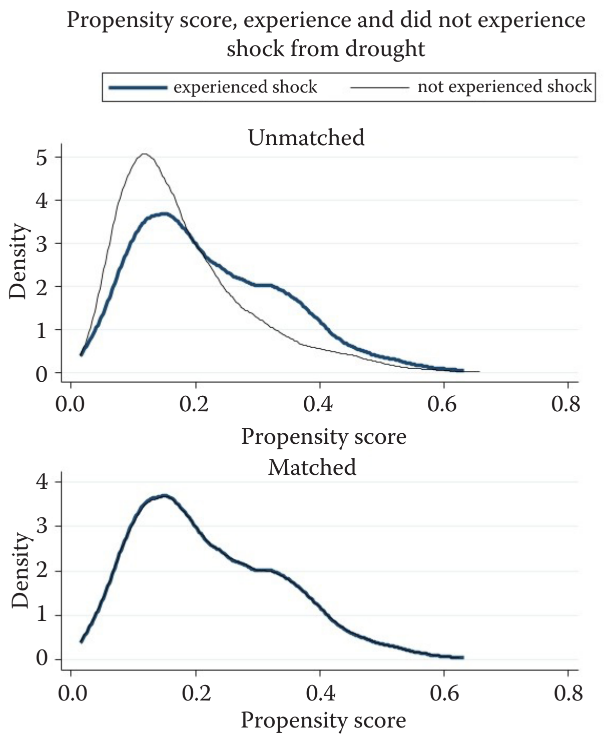

Figure 2. Distribution of propensity scores before and after matching for suffering sock from drought

Source: Author's elaboration

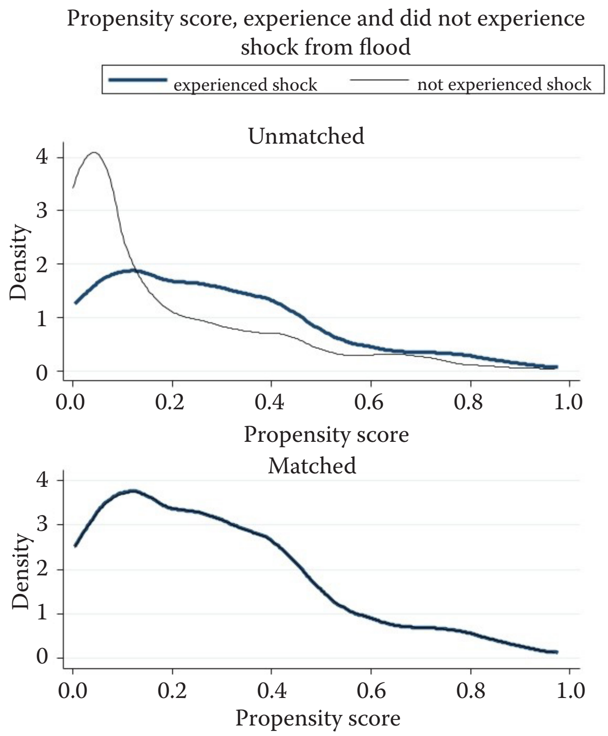

Figure 3. Distribution of propensity scores before and after matching for suffering sock from flood

Source: Author's elaboration

tion of chemical fertilisers since the households facing the shocks from climate change, such as floods, with the coefficient 0.070.

Among the social characteristics of rice farms, the study results provided some interesting factors that impacted technology adoption. Farmers with higher education levels tended to reduce the use of chemical fertilisers in rice production with a coefficient of –0.017 at the significance level of 5%. In addition, land fragmentation (Simpson index) negatively affected the adoption of the improved variety of rice with a coefficient of –0.456 at the significance level of 1%. However, the number of plots had a positive relationship to the adoption of improved seeds. This means that households with various large plots of rice production can encourage households to use improved seeds.

Discussion. The relationship between shock and technology adoption in agricultural production may be ambiguous because, with different shock events, farmers will adopt various measures to maximise benefits from agricultural production in the context of risk and uncertainty in production. A study by Gebremariam and Tesfaye (2018) indicateed that when households face a production shock, they reduce the probability of technology adoption, such as chemical fertiliser and improved seeds; however, they increase the investment in organic fertiliser. In addition, Arslan et al. (2017) find that households adopt more improved seeds and decrease the adoption of organic fertilisers since the farms face risk from weather shocks.

The main result of this study shows that shocks from climate change, such as drought, lead to the increased probability of technology adoption, such as improved seeds. This result is supported by the research of (Arslan et al. 2017), but contrasts with the others (Gebremariam and Tesfaye 2018). The reason is that improved seeds can yield substantial advantages if rice farms face dry conditions (Yang et al. 2024). According to Salgotra and Chauhan (2023), the utilisation of genetic enhancement techniques and the creation of rice varieties that can withstand drought and heat stress can lead to an increase in seed formation and boost the overall yield, even when the plants are exposed to stressful conditions. In addition, the application of polyamines from an external source has been discovered to enhance the ability of rice plants

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Table 4. The effect of shock from drought on technology adoption

Variables	Chemical fertilizer		Improved seeds		Organic fertilisers prepared by household		Organic fertilisers bought from others	
	before matching	after matching	before matching	after matching	before matching	after matching	before matching	after matching
Shock from drought	–0.016 (0.021)	–0.014 (0.019)	0.066* (0.034)	0.078*** (0.029)	0.054 (0.047)	0.043 (0.049)	0.053 (0.034)	0.061* (0.036)
Access to credit	–0.012 (0.017)	–0.019 (0.025)	0.047* (0.028)	0.064* (0.038)	–0.043 (0.039)	–0.129** (0.064)	–0.029 (0.028)	–0.061 (0.046)
Access to the Internet	–0.014 (0.016)	–0.007 (0.023)	–0.014 (0.025)	–0.021 (0.036)	–0.008 (0.036)	–0.012 (0.060)	–0.036 (0.025)	–0.044 (0.044)
Gender of household head	0.042 (0.044)	0.133** (0.067)	–0.049 (0.071)	–0.054 (0.103)	0.089 (0.102)	0.092 (0.182)	–0.042 (0.075)	0.035 (0.127)
Age of household head	0.000 (0.002)	–0.000 (0.003)	0.001 (0.003)	–0.001 (0.004)	–0.002 (0.004)	–0.006 (0.007)	–0.000 (0.003)	–0.011** (0.005)
Educational level of the household head	–0.003 (0.003)	–0.000 (0.005)	–0.001 (0.005)	–0.004 (0.007)	–0.007 (0.008)	0.000 (0.013)	0.008 (0.005)	0.003 (0.009)
Number of assets	0.005 (0.004)	0.007 (0.005)	–0.010* (0.006)	–0.013 (0.008)	–0.001 (0.008)	–0.017 (0.014)	0.003 (0.006)	0.016 (0.010)
Rice production area[1]	–0.004 (0.020)	0.058** (0.028)	0.039 (0.031)	–0.014 (0.043)	0.024 (0.044)	0.022 (0.072)	0.011 (0.031)	0.004 (0.052)
Fragmentation index	–0.070 (0.057)	–0.074 (0.080)	–0.207** (0.091)	–0.076 (0.123)	0.133 (0.126)	0.034 (0.202)	0.014 (0.090)	0.085 (0.149)
Changing land quality	0.010 (0.037)	0.029 (0.046)	–0.094 (0.059)	–0.003 (0.070)	0.139* (0.082)	0.160 (0.114)	0.086 (0.060)	–0.019 (0.087)
Number of plots	0.009 (0.006)	–0.006 (0.009)	0.020* (0.010)	0.013 (0.014)	0.019 (0.015)	0.008 (0.023)	0.005 (0.010)	0.001 (0.017)
Access to the agricultural extension service	0.024 (0.016)	0.023 (0.024)	0.013 (0.026)	0.035 (0.037)	0.057 (0.037)	0.049 (0.062)	0.001 (0.026)	0.060 (0.045)
Soil and water conservation	0.027 (0.019)	0.034 (0.026)	–0.053* (0.030)	–0.099** (0.040)	0.042 (0.042)	0.046 (0.068)	0.041 (0.030)	0.026 (0.048)
Access to irrigation	0.209*** (0.041)	0.180*** (0.054)	–0.057 (0.065)	–0.046 (0.084)	–0.147 (0.092)	0.034 (0.136)	–0.043 (0.065)	–0.108 (0.100)
Health risks	–0.012 (0.029)	0.022 (0.045)	–0.032 (0.048)	–0.043 (0.070)	–0.131* (0.067)	–0.159 (0.118)	0.018 (0.048)	–0.110 (0.084)
Number of family members	0.011 (0.007)	0.023** (0.011)	0.003 (0.012)	0.015 (0.017)	0.014 (0.017)	0.014 (0.029)	–0.009 (0.012)	–0.047** (0.021)
Constant	0.638*** (0.189)	0.168 (0.269)	0.630** (0.302)	1.094*** (0.415)	0.326 (0.424)	0.652 (0.692)	0.091 (0.300)	0.826* (0.498)
Fixed household ID	yes	yes	yes	yes	yes	yes	yes	yes
Fixed year	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1 347	400	1 356	403	1 300	384	1 329	391
Number of households	691	146	691	146	683	146	688	145

*,**,***significant at $P < 0.1$, $P < 0.05$, and $P < 0.01$, respectively; [1]in log form; SE in parentheses
Source: Author's elaboration

https://doi.org/10.17221/296/2024-AGRICECON

Table 5. The effect of shocks from flood on technology adoption

Variables	Chemical fertiliser		Improved seeds		Organic fertilisers prepared by household		Organic fertilisers bought from others	
	before matching	after matching	before matching	after matching	before matching	after matching	before matching	after matching
Shock from flood	0.056** (0.028)	0.070** (0.027)	–0.073 (0.045)	–0.100** (0.045)	0.065 (0.063)	0.048 (0.069)	0.073 (0.045)	0.054 (0.059)
Access to credit	–0.012 (0.017)	0.030 (0.034)	0.045 (0.027)	–0.027 (0.055)	–0.047 (0.039)	–0.087 (0.085)	–0.033 (0.028)	–0.042 (0.072)
Access to the Internet	–0.015 (0.016)	0.043 (0.028)	–0.013 (0.025)	0.033 (0.047)	–0.008 (0.036)	–0.069 (0.072)	–0.035 (0.025)	–0.059 (0.061)
Gender of household head	0.046 (0.044)	0.129 (0.087)	–0.055 (0.072)	–0.047 (0.144)	0.098 (0.103)	0.143 (0.244)	–0.033 (0.075)	–0.304 (0.194)
Age of household head	0.000 (0.002)	0.003 (0.004)	0.001 (0.003)	–0.001 (0.007)	–0.001 (0.004)	0.008 (0.011)	0.000 (0.003)	0.007 (0.009)
Educational level of the household head	–0.003 (0.003)	–0.017** (0.006)	–0.001 (0.005)	–0.016 (0.011)	–0.007 (0.008)	–0.008 (0.018)	0.008 (0.005)	0.002 (0.014)
Number of assets	0.004 (0.004)	0.005 (0.006)	–0.009* (0.006)	0.001 (0.010)	–0.001 (0.008)	–0.012 (0.016)	0.002 (0.006)	–0.013 (0.013)
Rice production area[1]	–0.002 (0.019)	0.005 (0.036)	0.034 (0.032)	0.119* (0.060)	0.023 (0.044)	0.132 (0.095)	0.011 (0.031)	0.017 (0.077)
Fragmentation index	–0.081 (0.057)	–0.038 (0.102)	–0.192** (0.091)	–0.456*** (0.168)	0.122 (0.126)	–0.028 (0.258)	–0.000 (0.091)	–0.069 (0.218)
Changing land quality	0.009 (0.037)	–0.061 (0.055)	–0.094 (0.060)	–0.151 (0.092)	0.136* (0.082)	0.036 (0.142)	0.081 (0.060)	0.096 (0.122)
Number of plots	0.009 (0.006)	0.029** (0.012)	0.020* (0.010)	0.038** (0.019)	0.019 (0.015)	0.015 (0.030)	0.005 (0.010)	–0.005 (0.024)
Access to the agricultural extension service	0.018 (0.017)	–0.031 (0.033)	0.020 (0.027)	0.072 (0.054)	0.053 (0.038)	0.083 (0.086)	–0.006 (0.027)	0.030 (0.071)
Soil and water conservation	0.024 (0.018)	–0.005 (0.036)	–0.042 (0.029)	0.057 (0.060)	0.047 (0.042)	0.005 (0.092)	0.049* (0.029)	0.002 (0.078)
Access to irrigation	0.213*** (0.041)	0.309*** (0.101)	–0.064 (0.065)	–0.279* (0.167)	–0.143 (0.092)	–0.095 (0.251)	–0.038 (0.065)	–0.242 (0.214)
Health risks	–0.008 (0.029)	0.061 (0.062)	–0.040 (0.048)	–0.016 (0.102)	–0.134** (0.067)	–0.163 (0.174)	0.019 (0.048)	0.032 (0.134)
Number of family members	0.012 (0.007)	0.008 (0.014)	0.002 (0.012)	0.009 (0.023)	0.013 (0.017)	0.051 (0.035)	–0.009 (0.012)	–0.001 (0.029)
Constant	0.607*** (0.189)	0.167 (0.365)	0.678** (0.303)	0.427 (0.601)	0.314 (0.424)	–0.943 (0.923)	0.063 (0.301)	0.332 (0.774)
Fixed household ID	yes	yes	yes	yes	yes	yes	yes	yes
Fixed year	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1 347	241	1 356	242	1 300	232	1 329	238
Number of households	691	89	691	89	683	89	688	89

*,**,***significant at $P < 0.1$, $P < 0.05$, and $P < 0.01$, respectively; [1]in log form; SE in parentheses
Source: Author's elaboration

https://doi.org/10.17221/296/2024-AGRICECON

to withstand drought. This is achieved by improving the water content of the leaves, enhancing photosynthesis, and enhancing the characteristics of the plant's membranes. As a result, the overall performance of the crop is increased (Farooq et al. 2009). In addition, this study finds that households tend to adopt technology such as organic fertiliser under the shock of drought. The result is linked to the previous research (Gebremariam and Tesfaye 2018). The occurrence of drought poses a substantial obstacle to the cultivation of rice, impacting both the quantity and efficiency of crop production. Farmers are progressively adopting organic fertilisers as a tactic to mitigate the effects of drought on rice growth. Organic fertilisers provide several advantages in drought conditions as they can improve soil structure, enhance water retention capacity, increase nutrient availability to plants, and stimulate beneficial microbial activity in the soil. These factors contribute to better water stress management (Zain et al. 2014; Sukanteri et al. 2022).

Another finding in this study is the positive relationship between shock from flood and use of chemical fertiliser. Floods can result in substantial losses for rice producers, such as the mortality of sown rice seeds, crop failures, and the displacement of paddy rice output by flood currents (Pirngadi et al. 2024). To minimise the negative effects of flooding on crop yields, it is essential to comprehend the impact of flooding stress on crops and devise enhanced production techniques that bolster the ability of cropping systems to withstand extreme weather events (Kaur et al. 2020). In addition, shock from floods leads to a reduced probability of using improved varieties in rice production. Rice farming households are frequently compelled to pursue new means of income as a result of the detrimental effects of floods on their household income, highlighting their susceptibility (Yamin and Putri 2024). In addition, floods might result in a decrease in rice production, which has a negative impact on farmers' earnings and the general stability of the food supply.

CONCLUSION

Emphasising the importance of sustainable rice cultivation is essential for a rice-exporting nation such as Vietnam since it not only contributes to the gross domestic product but also ensures food security domestically. Technology can be a key to promoting rice production and ensuring sustainable development in the rice sector. However, experiencing shocks from climate change can make farmers change their behaviour in the adoption of technology, such as chemical fertiliser, improved seeds, and organic fertiliser. In this study, finding a correlation between feeling shock and technological adoption is crucial in the field of economic growth, as it can significantly improve productivity and sustainability.

This study aims to explore farmer behaviour in technology adoption since they suffer the shock from climate change, such as floods or drought in rice production in Vietnam. With the panel data from VARHS 2012–2018, fixed effect estimation with a propensity score matched sample controls for selection issues was used to identify the impact of shocks from flood or drought on technology adoption, such as chemical fertiliser, improved seeds, and organic fertiliser. The results showed that rice farmers experiencing shock from drought tended to adopt improved rice seeds and buy organic fertiliser from others. In addition, farmers would use more chemical fertiliser since their rice farms suffered shock from floods. However, the study found a negative relationship between shock from flood and technology adoption, such as improved seeds. Overall, the findings emphasised the significance of adopting technology to improve productivity, welfare, and risk management. The study revealed that shocks impeded households' adoption of complementary technologies. Following shocks, farmers may selectively adopt innovations strategically, leading to long-term consequences that extend beyond food security. Efforts to promote the adoption of agricultural innovation should include developing strategies to mitigate the impact of sudden changes on farming families.

Although the estimates control for selection bias as far as possible, there are limitations to the above analysis. Firstly, it is important to note that even though the fixed effect estimation with a propensity score matched sample effectively addresses selection issues, the matched sample still exhibits notable disparities between individuals who have experienced shock and those who have not. These differences are evident in various aspects such as the number of assets (as indicated in Tables 2 and 3), access to credit, gender of household head, number of plots, access to the agricultural extension service, and access to irrigation (Table 3). Second, the data did not provide clear information about the input quantity for each plot; therefore, we cannot see how rice farmers change their behaviours regarding technology adoption (full adoption or partial adoption) since farmers suffer shock from climate change. In addition, the result cannot be provided to the individual provinces because observations in some provinces cannot be enough for estimation. Future research could

https://doi.org/10.17221/296/2024-AGRICECON

utilise plot-level data to enhance causal inference regarding the impact of shock on suffering and the adoption of technology in rice cultivation.

REFERENCES

Abate G.T., Francesconi G.N., Getnet K. (2014): Impact of agricultural cooperatives on smallholders' technical efficiency: Empirical evidence from Ethiopia. Annals of Public and Cooperative Economics, 85: 257–286.

Ambong R.M.A. (2022): Methods of rice technology adoption studies in the Philippines and other Asian countries: A systematic review. Research on World Agricultural Economy, 3: 15–24.

Arslan A., Belotti F., Lipper L. (2017): Smallholder productivity and weather shocks: Adoption and impact of widely promoted agricultural practices in Tanzania. Food Policy, 69: 68–81.

Asfaw A., Admassie A. (2004): The role of education on the adoption of chemical fertiliser under different socioeconomic environments in Ethiopia. Agricultural Economics, 30: 215–228.

Asfaw S., Shiferaw B., Simtowe F., Lipper L. (2012): Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. Food Policy, 37: 283–295.

Asfaw S., Scognamillo A., Di Caprera G., Sitko N., Ignaciuk A. (2019): Heterogeneous impact of livelihood diversification on household welfare: Cross-country evidence from Sub-Saharan Africa. World Development, 117: 278–295.

Becker S.O., Ichino A. (2002): Estimation of average treatment effects based on propensity scores. The Stata Journal, 2: 358–377.

Belayneh M. (2023): Factors affecting the adoption and effectiveness of soil and water conservation measures among small-holder rural farmers: The case of Gumara watershed. Resources, Conservation and Recycling Advances, 18: 200159.

Branco D., Féres J. (2021): Weather shocks and labor allocation: Evidence from rural Brazil. American Journal of Agricultural Economics, 103: 1359–1377.

Bukchin S., Kerret D. (2018): Food for hope: The role of personal resources in farmers' adoption of green technology. Sustainability, 10: 1615.

Diagne A., Tamini L.D., Fall F.S. (2022): Factors explaining the dynamics of agricultural technological innovations adoption: Evidence from Senegal's rain maize farmer. Agricultural Sciences, 13: 1234–1258.

Duong P.B., Thanh P.T. (2019): Adoption and effects of modern rice varieties in Vietnam: Micro-econometric analysis of household surveys. Economic Analysis and Policy, 64: 282–292.

Emmanuel D., Owusu-Sekyere E., Owusu V., Jordaan H. (2016): Impact of agricultural extension service on adoption of chemical fertilizer: Implications for rice productivity and development in Ghana. NJAS: Wageningen Journal of Life Sciences, 79: 41–49.

Farooq M., Wahid A., Lee D.J. (2009): Exogenously applied polyamines increase drought tolerance of rice by improving leaf water status, photosynthesis and membrane properties. Acta Physiologiae Plantarum, 31:937–945.

Farooq M.S., Riaz S., Abid A., Abid K., Naeem M.A. (2019): A survey on the role of IoT in agriculture for the implementation of smart farming. IEEE Access, 7: 156237–156271.

Gebremariam G., Tesfaye W. (2018): The heterogeneous effect of shocks on agricultural innovations adoption: Microeconometric evidence from rural Ethiopia. Food Policy, 74: 154–161.

Grabrucker K., Grimm M. (2021): Is there a rainbow after the rain? How do agricultural shocks affect non-farm enterprises? Evidence from Thailand. American Journal of Agricultural Economics, 103: 1612–1636.

Ha V.H., Mizunoya T., Kien N.D., Dung T.Q., An L.T., Phan N.T., Tan N.Q., Tien P.T.T., Dinh N.C. (2022): Post-flood recovery in the central coastal plain of Vietnam: Determinants and policy implications. Asia-Pacific Journal of Regional Science, 6: 899–929.

Heckman J.J., Ichimura H., Todd P.E. (1997): Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. The Review of Economic Studies, 64: 605–654.

Holden S.T., Quiggin J. (2017): Climate risk and state-contingent technology adoption: Shocks, drought tolerance and preferences. European Review of Agricultural Economics, 44: 285–308.

Hossain M., Bose M.L., Mustafi B.A. (2006): Adoption and productivity impact of modern rice varieties in Bangladesh. The Developing Economies, 44: 149–166.

Kaur G., Singh G., Motavalli P.P., Nelson K.A., Orlowski J.M., Golden B.R. (2020): Impacts and management strategies for crop production in waterlogged or flooded soils: A review. Agronomy Journal, 112: 1475–1501.

Khandker S., Koolwal G.B., Samad H. (2009): Handbook on Impact Evaluation. Washington D.C., World Bank: 239.

Kien N.D., Dung T.Q., Oanh D.T.K., An L.T., Dinh N.C., Phan N.T., Nga L.T.T. (2023): Climate-resilient practices and welfare impacts on rice-cultivating households in Vietnam: Does joint adoption of multiple practices matter? Australian Journal of Agricultural and Resource Economics, 67: 263–284.

Komarek A.M., De Pinto A., Smith V.H. (2020): A review of types of risks in agriculture: What we know and what we need to know. Agricultural Systems, 178: 102738.

https://doi.org/10.17221/296/2024-AGRICECON

Kumar A., Takeshima H., Thapa G., Adhikari N., Saroj S., Karkee M., Joshi P.K. (2020): Adoption and diffusion of improved technologies and production practices in agriculture: Insights from a donor-led intervention in Nepal. Land Use Policy, 95: 104621.

Li L., Gao Y., Wang X. (2023): Impact of economic policy uncertainty on agribusiness technology innovation: Evidence from 231 listed firms in China. Sustainability, 15: 10037.

Mehar M., Mittal S., Prasad N. (2016): Farmers coping strategies for climate shock: Is it differentiated by gender? Journal of Rural Studies, 44: 123–131.

Michler J.D., Baylis K., Arends-Kuenning M., Mazvimavi K. (2019): Conservation agriculture and climate resilience. Journal of Environmental Economics and Management, 93: 148–169.

Nguyen D.K., Nguyen P., Nguyen H.M., Dang T.A.T. (2024): Examining the impact of climate information access on adaptive behaviors during heatwaves: Insights from Central Vietnam. Journal of Public Health and Development, 22: 100–116.

Nguyen Chau T., Scrimgeour F. (2022).: Productivity impacts of hybrid rice seeds in Vietnam. Journal of Agricultural Economics, 73: 414–429.

Phan N.T., Lee J., Kien N.D. (2022a): The impact of land fragmentation in rice production on household food insecurity in Vietnam. Sustainability, 14: 11162.

Phan N.T., Pabuayon I.M., Kien N.D., Dung T.Q., An L.T., Dinh N.C. (2022b): Factors driving the adoption of coping strategies to market risks of shrimp farmers: A case study in a coastal province of Vietnam. Asian Journal of Agriculture and Rural Development, 12: 65–74.

Pirngadi R.S., Rahmawaty, Ayu S.F., Rauf A. (2024): Estimation of loss of rice farmers due to flood at Krueng Kluet Watershed (with the eclac method approach). IOP Conference Series: Earth and Environmental Science, 1302: 012125.

Salgotra R.K., Chauhan B.S. (2023): Ecophysiological responses of rice (*Oryza sativa* L.) to drought and high temperature. Agronomy, 13: 1877.

Shi Y., Siddik A.B., Masukujjaman M., Zheng G., Hamayun M., Ibrahim A.M. (2022): The antecedents of willingness to adopt and pay for the IoT in the agricultural industry: An application of the UTAUT 2 theory. Sustainability, 14: 6640.

Sukanteri N.P., Diah Yuniti I.G.A., Suryana I.M., Verrawati Y. (2022): Efficiency in the use of rice farming organic inputs to promote food security. KnE Life Sciences, 7: 479–486.

Tambo J.A., Wünscher T. (2017): Enhancing resilience to climate shocks through farmer innovation: Evidence from northern Ghana. Regional Environmental Change, 17: 1505–1514.

Tan T., Sarkar A., Rahman A., Qian L., Hussain Memon W., Magzhan Z. (2021): Does external shock influence farmer's adoption of modern irrigation technology? Land, 10: 882.

Tesfay M.G. (2021): Impact of irrigated agriculture on welfare of farm households in northern Ethiopia: Panel data evidence. Irrigation and Drainage, 70: 306–320.

Tran T.Q., Van Vu H. (2019): Land fragmentation and household income: First evidence from rural Vietnam. Land Use Policy, 89: 104247.

UNU Wider (2024): Viet Nam data. [Dataset.] Available at https://www.wider.unu.edu/database/viet-nam-data (accessed Mar 1, 2024).

Usman M., Hameed G., Saboor A., Almas L.K., Hanif M. (2021): R&D innovation adoption, climatic sensitivity, and absorptive ability contribution for agriculture TFP growth in Pakistan. Agriculture, 11: 1206.

Wang Z., Liu J., Li T., Chao J., Gao X. (2021): Factors affecting new agricultural business entities' adoption of sustainable intensification practices in China: Evidence from the main apple-producing areas in the Loess Plateau. Agronomy, 11: 2435.

Yamin M., Putri N.E. (2024): Agricultural household economic in condition flood impact of climate change in Indonesia. IOP Conference Series: Earth and Environmental Science, 1364: 012017.

Yang B., Chen S., Zheng Z., Zeng J., Liu J., Zhao H., Zheng Y. (2024): Genome-wide association studies for rice seed germination under drought stress using 3VmrMLM. Food and Energy Security, 13: e529.

Zain N., Ismail M., Mahmood M., Puteh A., Ibrahim M. (2014): Alleviation of water stress effects on MR220 rice by application of periodical water stress and potassium fertilization. Molecules, 19: 1795–1819.

Zhang H., Li J., Quan T. (2023): Strengthening or weakening: The impact of an aging rural workforce on agricultural economic resilience in China. Agriculture, 13: 1436.

Received: August 19, 2024
Accepted: November 25, 2024
Published online: January 24, 2025